Energy-Efficient Optimal Opportunistic Forwarding for Delay-Tolerant Networks

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***Abstract*—Due to the uncertainty of transmission opportunities between mobile nodes, the routing of delay-tolerant networks (DTNs) exploits the mechanism of opportunistic forwarding. Efficient algorithms and policies for opportunistic forwarding are crucial for maximizing the message delivery probability while reducing the delivery cost. In this paper, we investigate the problem of energy-efficient opportunistic forwarding for DTNs. First, we model the message dissemination by introducing a continuous-time Markov framework. Based on this framework, we formulate the optimization problem of opportunistic forwarding, with the constraint of energy consumed by the message delivery for both two-hop and epidemic forwarding. Then, based on the solution of the optimization problem, we design different kinds of forwarding policies such as static and dynamic policies. Among these policies, we find that the threshold dynamic policy is optimal for both two-hop and epidemic forwarding. By simulation results, we show the accuracy of our continuous-time Markov analysis model. Furthermore, through extensive numerical results, we demonstrate that the performance of the threshold dynamic policy is the best among the static and continuous dynamic policies, and among the continuous dynamic policies, the negative-power policy provides relatively better performance.**

***Index Terms*—Delay-tolerant networks (DTNs), energy-efficient forwarding, opportunistic forwarding.**

I. Introduction

To PROVIDE communication services in the highly challenged wireless networks, such as vehicular ad hoc networks for road safety and commercial applications [1]–[4], sparse sensor networks for wildlife tracking and habitat monitoring [5], deep-space interplanetary networks [6], and mobile social networks [7], where there is only intermittent connectivity, delay/disruption-tolerant networks (DTNs) are proposed. For example, in the vehicular DTN, the nodes are vehicles, and they move very quickly. Therefore, the network is highly mobile and frequently disconnected, and it is unrealistic to maintain end-to-end paths between any communication source and destination pairs. Consequently, traditional ad hoc routing protocols, which rely on the end-to-end paths [8], may fail to work. As a result, researchers propose a new routing mechanism called store–carry–forward routing [9]–[11] to provide communication. Store–carry–forward routing exploits the opportunistic connectivity and node mobility to relay and carry messages, respectively, around the networks. When the next hop is not immediately available for the current node to forward a message, it will store the message in its buffer, carry the message along the movement, and transmit it to other appropriate nodes until it gets a communication opportunity, which further helps forward the message.

Due to the randomness of the intermittent connectivity between two mobile nodes, DTN routing algorithms replicate messages to keep many copies of the same message in different nodes to increase the message delivery probability. The most typical algorithm is epidemic routing [12], in which packets that arrive at the intermediate nodes are forwarded to all neighbors. Although this flooding-based scheme can achieve high delivery probability, it wastes much energy and suffers from poor scalability in large networks. Therefore, much effort has been focused on opportunistic forwarding (or probabilistic forwarding) algorithms, which try to reduce the number of message replications while maintaining relatively high delivery probability. For example, Groenevelt and Nain [13] propose a two-hop forwarding algorithm, in which only the source node of the message can replicate it, whereas the other nodes can only forward it to the destination node. Haas *et al.* [14] propose a gossip forwarding algorithm by using a probability to determine the message transmissions in epidemic routing, and Spyropoulos *et al.* in [15] propose a family of Spray routing algorithms. These opportunistic forwarding algorithms can achieve high delivery probability when the energy for the message transmissions is not constrained. However, in several DTNs, the energy is limited. For example, in wireless mobile sensor networks for environmental and wildlife behavior monitoring [16], the sensor nodes are attached to animals such as zebras [17] and deer [18]. The mobile sensor nodes form the DTN, and consequently, the energy will be a serious issue. Another example is human-network-like pocket switched networking (PSN) [19], where mobile users, because they are the networking nodes, use their mobile devices, which

Manuscript received February 1, 2010; revised May 21, 2010; accepted July 16, 2010. Date of publication August 30, 2010; date of current version November 12, 2010. This work was supported in part by the National Major Scientific and Technological Specialized Project under Grant 2010ZX03004-002-02, the National Basic Research Program under Grant 2007CB310701, and the National High-Technology Research and Development Program under Grant 2008AA01Z107 and Grant 2008AA01A331, by the Program for Changjiang Scholars and Innovative Research Team in University, and by Tsinghua National Laboratory for Information Science and Technology. Part of this paper was presented at the IEEE International Conference on Communications, Cape Town, South Africa, May 2010. The review of this paper was coordinated by Prof. H. Hassanein.

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Digital Object Identifier 10.1109/TVT.2010.2070521

are energy constrained. Therefore, it is necessary to design energy-efficient opportunistic forwarding algorithms, which save energy consumption for the message delivery. Furthermore, even for networks such as vehicular DTNs, where energy is typically not an issue, unnecessary message transmissions and flooding are not good for the common welfare of the whole network, because transmissions also cause contentions to other users. Therefore, energy-efficient forwarding algorithms not only affect the energy consumption but influence the overall network throughput as well.

In this paper, we investigate the problem of optimal opportunistic forwarding for DTN with the constraint of energy for message delivery. We consider the two most popular routing algorithms: 1) two-hop forwarding and 2) epidemic forwarding. To achieve the maximum delivery probability under the condition that the energy for message transmissions is limited by a threshold, we control the probability of transmitting a message upon the opportunistic connectivity. Therefore, our goal is to maximize the message delivery probability while satisfying the energy constraint. The contributions can be summarized as follows.

- We introduce a continuous-time Markov framework to model the message dissemination in DTN. To our best knowledge, we are the first to use the continuous-time Markov chain to model the opportunistic forwarding. Because the proposed model appropriately characterizes both the message dissemination and the energy constraint, it significantly simplifies the formulated optimization problem.
- We formulate an optimization problem that is applicable to both two-hop and opportunistic epidemic forwarding. Based on the property of the optimization problem, we derive the static policy, the continuous dynamic policy, and the threshold dynamic policy, which satisfy the defined energy constraint for message delivery, and theoretically prove that the threshold dynamic policy is optimal for both two-hop and epidemic forwarding.
- By comparing the simulation results with the theoretical results, we show that our continuous-time Markov model is accurate in characterizing the system performance, whose deviation from the simulation results is only about 4%. Through extensive numerical results, we study the properties of static and dynamic policies for both two-hop and epidemic forwarding. Based on the results, we demonstrate that the threshold dynamic policy is the optimal policy and find that the negative-power-function-based continuous dynamic policy is more suitable for opportunistic forwarding control, which obtains a higher delivery probability. Based on the results of probabilistic epidemic forwarding, we find that the static policy is even better than the exponential policy.
- Under the same energy constraint, we compare the performance of two-hop and epidemic forwarding. Usually, epidemic forwarding provides better performance under the optimal threshold policy. However, we obtain an unexpected result that two-hop forwarding performs better than the epidemic forwarding under the static policy when the message's lifetime is short.

The rest of this paper is organized as follows. After presenting the related work in Section II, we describe the system model and give the problem statement in Section III. In Section IV, we formulate an optimization problem for both two-hop and probabilistic epidemic forwarding. Based on the formulated problem, in Section V, we design different kinds of policies, including the static policy, the continuous dynamic policy, and the threshold dynamic policy and theoretically prove that the threshold policy is the optimal policy for both two-hop and epidemic forwarding. Then, we introduce the performance evaluation environment and analyze the numerical results in Section VI. Finally, we conclude this paper in Section VII.

II. Related Work

Over the past few years, several routing and forwarding algorithms have been proposed to improve the performance of DTN routing. Epidemic routing [12] is a flooding-based protocol. In epidemic routing, the node floods the messages to all its neighbors when the communication opportunity comes. The main problem with epidemic routing is the high demand of network resources, such as energy, network bandwidth, and storage. Therefore, its scalability and efficiency is limited in large-scale networks. A number of approaches have been proposed to reduce its overhead [3], [10], [14], [15], [19]–[21]. Haas *et al.* [14] propose a gossip-based routing. It uses a probability to determine the message transmissions. Spyropoulos *et al.* [15] propose a new family of Spay and focus routing protocols, which spay a few message replicates into the networks and then deliver each copy toward the destination. It shows that Spay and focus not only significantly improve the transmissions probability per message but also reduce the average delivery delay. Burgess *et al.* [3] propose MaxProp based on prioritizing the schedule of packets to be dropped. Among the aforementioned approaches, some opportunistic forwarding (or probabilistic forwarding)-based approaches rely on probability metrics such as the time that elapsed since the last encounter [20], social similarity [19], and geometric distance [21]. These forwarding algorithms try to achieve the optimal system performance without considering the energy constraint, and their optimal cannot be guaranteed. However, our proposed opportunistic forwarding policies are the optimal solution, which is demonstrated by both theoretical proof and numerical results.

Recently, a number of forwarding algorithms have been proposed to achieve the optimal system performance. Krifa, Barakat, and Spyropoulos [22], [23] propose an efficient optimal message-dropping policy and forwarding schedule algorithm based on the global knowledge of the network to minimize the average delivery delay or to maximize the average delivery rate. Hay and Giaccone in [24] study the optimal time-independent graph-based algorithms for deterministic and centralized DTN, where the contact time between nodes is known in advance or can be predicted. To solve the overhead problem of the epidemic-style algorithms, Nelson *et al.* [25] propose an encounter-based routing protocol to maximize the message delivery ratio. Liu and Wu [26] provide an optimal forwarding protocol to maximize the delivery probability based on a particular knowledge about the network. Reich and Chaintreau [27] propose an optimal content allocation scheme in the global distribution cache and develop a reactive distributed algorithm to achieve the global cache toward the optimal allocation without the use of any explicit estimators or control channel information. However, all these optimal forwarding and allocation algorithms do not consider the energy constraint.

The work reported in [28], which studies the optimal decentralized stochastic control issues with the energy constraint for DTN (DSC–DTN), is close to this paper. The aforementioned paper introduces a discrete-time model to model the message dissemination in DTN and analyzes the optimal policies for routing control by sample path techniques. To our best knowledge, it is the only published work, until now, to study the problem of energy-constrained optimal opportunistic forwarding. However, there are important differences compared with this paper. First, we use a continuous-time Markov model. Unlike the discrete-time model, in which the nodes are assumed to be able to forward packets only in every discrete time slot, the continuous-time model allows the nodes to forward packets at any time. Second, in the aforementioned paper, the only considered routing protocol is two-hop forwarding. In this paper, we also study probabilistic epidemic forwarding and formulate a uniform optimization problem for both two-hop and epidemic forwarding. Third, in this paper, we consider different kinds of forwarding policies, such as continuous power and exponential policies, and extensively compare their performance. Another important contribution is that our closed-form expressions for the system performance are much more accurate than in [28].

In the related work on mobility models, because the intercontact time (*ICT*) of mobile nodes is an important factor in influencing DTN routing performance and end-to-end delay, there have been several studies to characterize it. Early works are model-based studies. For example, the authors of [29] and [30] find that the ICTs of the random-waypoint, random-mobility, and Brownian motion models follow exponential distribution. Later, some works [31]–[34] on the empirical results by analyzing extensive human mobility traces indicate that the tail behavior of ICT is far from being exponential but is close to the power-law distribution, although the decay is exponential [34]. In the last two years, as vehicle ad hoc networks have become an increasingly important application of DTN, the authors of [35] and [36] model the ICT between vehicles. The exponential ICT of vehicles is recognized, which is in sharp contrast to the works based on human mobility. In this paper, we use the exponential ICT model. The reason is that this model takes effect in several scenes as previously described; furthermore, it enables the tactical analysis.

III. System Model and Problem Statement

We model the DTN as a set of wireless mobile nodes, which are denoted by V, $|V| = N(N > 2)$, which means that the number of the nodes is N. The density of the nodes is assumed to be sparse, and they can communicate only when they move into the transmission range of each other, which means a communication contact. All nodes independently move in the network, and their mobility models are assumed to be independent and identically distributed (*i.i.d.*). Consequently, *ICT*, as defined in *Definition 1*, is also *i.i.d.* Recent studies that focus on well-known mobility models, such as random waypoint and random direction [29], find that the distribution of ICT is exponential. Therefore, the ICT in our model is assumed to be exponentially distributed with parameter λ, which is equal to $1/E(ICT)$. This assumption is validated by works on studying the mobility behaviors of both human and vehicles [34], [35], which are the most typical nodes in the DTNs of mobile social networks and vehicle networks, respectively [11]. For example, [35] and [36] model the ICT between vehicles, and [34] partially models the ICT of humans. They all reveal the exponential distribution of the ICT between nodes by analyzing a large amount of real mobility traces.

Definition 1—ICT: The ICT of node i and node $j(ICT_{i,j})$ is defined as the time that it takes them to again come within the range of each other from the last time that they were moving out of range of each other (t_0), i.e., $ICT_{i,j} = \min_t(t - t_0) : \|L_i(t) - L_j(t)\| \le R$, $t > t_0$, where $L_i(t)$ and $L_j(t)$ are the locations of nodes i and j at time t, respectively, and R is the transmission range.

In the network, there is a source node, which generates messages to the network. We assume that a message is created in time 0 and its lifetime is T. It means that, after time T, all nodes in the network should discard it. Therefore, the goal of the optimal opportunistic forwarding policies is to try to transmit the message to the destination before time T. We investigate two typical forwarding algorithms—two-hop forwarding and probabilistic epidemic forwarding—which are described as follows.

Two-hop forwarding. In two-hop forwarding, the source node can replicate the message to any other nodes, but other nodes can only forward it to the destination. When a communication contact between the source node and any other nodes, except the destination arises, at time t occurs, we assume that the source node forwards the message with probability $p(t) \in [0, 1]$.

Probabilistic epidemic forwarding. In probabilistic epidemic forwarding, when one node with the message comes into the communication range of another node without the message, except the destination, at time t, it forwards the message to the node with probability $p(t) \in [0, 1]$.

In the aforementioned two forwarding algorithms, $p(t)$ is the control variable that achieves the optimal performance while satisfying the energy constraint. The algorithms can be classified as static or dynamic policies, including the continuous dynamic policy and the threshold dynamic policy, which are defined in *Definition 2*. Different policies can be applied to different network environments. For example, the static policy is used when the network designers already know the appropriate value for the probability of transmission or when the system does not need to make any decision but needs to follow a predefined value. In terms of the applications of the static policy, the most typical approach is the gossip forwarding algorithm [14], where each node forwards a message with some probability to reduce the overhead of the routing protocols.

On the other hand, the dynamic policy is a more intelligent approach, which considers the network dynamic. For instance, in [37], the threshold dynamic policy is intelligently used by attackers to inflict the maximum damage of malware on the network.

Definition 2—Static Policy and Dynamic Policy: $p(t)$ is a static policy if it is a constant denoted by $p(t) = \alpha$, which means that it does not change with time t. Otherwise, it is a dynamic policy. A policy $p(t)$ is a continuous dynamic policy if it is a continuous function of time t. A policy $p(t)$ is a threshold dynamic policy if $\exists t_0 > 0$ as a threshold such that $p(t) = 1$ for $t \le t_0$ and $p(t) = 0$ for $t > t_0$.

In the network, there will be many different messages. However, in this paper, we will only consider one message for a certain duration, the results of which can be extended to multimessages. Let $X(t)$ denote the number of message copies in all nodes, including the original message in the source node at time $t(X(0) = 1)$ and stochastic process $X = \{X(t), t \ge 0\}$. Therefore, $X(t)$ is related to the transmission times of the message. Considering the energy consumption for delivering the message to the destination, we assume that it is proportional to the expected number of transmission times during the message's lifetime, where the energy consumption of one time transmission includes both the reception energy at the receiving node and the sending energy at the transmitting node. Therefore, it can be expressed as follows: $\gamma(E(X(T)) - 1) \le Q$, where Q is the total energy constraint for delivering the message, γ is a positive multiplicator, and 1 is subtracted, because the message copy in the source node needs no transmission. Without loss of generality, we assume that $\gamma = 1$. For simplicity, we redefine the energy constraint for the message delivery as follows: $E(X(T)) \le \Psi$, where $\Psi = Q/\gamma + 1 = Q + 1$. In our model, we notice that we only consider the communication energy for message transmission and reception, which is the main energy consumption in the system [17]. Because we limit the total energy consumption for delivering a message, the number of transmissions is constrained. Therefore, our energy-efficient optimal forwarding scheme is concerned with how the number of transmissions can be reduced.

Based on the definition of $X(t)$, we note that $X(t)$ satisfies the following equation:

$$
\begin{aligned}
P\{X(t_{n+1}) = i_{n+1} | X(t_k) = i_k, 0 \le k \le n\} \\
= P\{X(t_{n+1}) = i_{n+1} | X(t_n) = i_n\}
\end{aligned}
$$

where any $0 \le t_0 < t_1 < \cdots < t_{n+1}$, $i_k \in [1, N] (0 \le k \le n+1)$. Therefore, X is a continuous-time Markov chain.

Let $F(t)$ denote the probability that the message has been delivered to the destination at time t. Because our goal is to transmit the message to the destination before the lifetime T, we should maximize $F(T)$. The restriction is the available energy. Therefore, the problem of the optimal opportunistic forwarding policy with the energy constraint for message delivery can be expressed as the following optimization problem:

$$
\begin{aligned}
&\text{Maximize} \quad F(T) \\
&\text{Subject to} \quad E(X(T)) \le \Psi. \qquad (1)
\end{aligned}
$$

TABLE I
LIST OF COMMONLY USED VARIABLES

Variable	*Description*
N	Number of nodes in the network
ICT	Inter-Contact time of any two nodes
λ	Exponential parameter of ICT
T	Lifetime of the message
$p(t)$	Transmission probability at the time t
$X(t)$	Number of message copies in the network
Q	Original energy constraint, maximum expected number of infected nodes
Ψ	Energy constraint, $\Psi = Q/\gamma + 1$
$F(t)$	Probability that the message has been delivered to the destination at the time t
$\varphi_{t,t+\Delta t}(j)$	Indicator that the node j receive the message from the source within the time $[t, t+\Delta t]$
$H(t)$	Probability that the message has not been delivered to the destination at the time t

In Sections IV and V, we will investigate the aforementioned optimization problem and the solution for both two-hop and epidemic forwarding. In Table I, the variables and their notations that were commonly used throughout this paper are summarized.

IV. Optimization Formulation

A. Two-Hop Forwarding

In this section, we concentrate on the optimal opportunistic forwarding problem under two-hop forwarding, in which the control policy $p(t)$ maximizes $F(T)$ while satisfying the energy constraint $E(X(T)) \le \Psi$.

We note that X is a continuous-time Markov chain; therefore, let us first characterize the evolution of its state variable $X(t)$. We consider this problem at time t. First, we define the random variable $\varphi_{t,t+\Delta t}(j)$ as the indicator that node j without the message receives it within time interval $[t, t+\Delta t]$ as follows:

$$
\varphi_{t,t+\Delta t}(j) = \begin{cases} 1, & \text{if node } j \text{ receives the message within } \Delta t \\ 0, & \text{otherwise.} \end{cases}
$$

In two-hop forwarding, node j can receive the message only from the source node. If $\varphi_{t,t+\Delta t}(j) = 1$, node j should encounter the source node, for which the probability is $(1 - e^{-\lambda \Delta t})$, and the source node should choose to transmit the message to node j. Thus, we have

$$
\mathrm{P}\{\varphi_{t,t+\Delta t}(j) = 1\} = (1 - e^{-\lambda\Delta t}) p(t + \Delta t).
$$

Therefore, its expectation can be obtained as follows:

$$
\begin{aligned}
E(\varphi_{t,t+\Delta t}(j)) &= 1 \times q + 0 \times (1 - q) \\
&= (1 - e^{-\lambda\Delta t}) p(t + \Delta t) \qquad (2)
\end{aligned}
$$

where $q = \mathrm{P}\{\varphi_{t,t+\Delta t}(j) = 1\}$.

At the same time, we can have the following equation:

$$
X(t + \Delta t) = X(t) + \sum_{j=1}^{N - X(t)} \varphi_{t,t+\Delta t}(j). \qquad (3)
$$

其实 \dot{I} = \beta*(N-I) 的详细解释；
可以放到我们的论文里；
2007CN也有提供这样的论证

Based on (2) and (3), we can derive the expected value of $X(t)$ as follows:

$$E(X(t+\Delta t)) = E(X(t)) + (N - E(X(t)))\, E(\varphi_{t,t+\Delta t}(j))$$

$$\dot{E}(X(t)) = \lim_{\Delta t \to 0} \frac{(N - E(X(t)))\,(1 - e^{-\lambda \Delta t}) p(t+\Delta t)}{\Delta t} = (N - E(X(t)))\, \lambda p(t).$$

Now, we have obtained the ordinary differential equation for $E(X(t))$. We solve this equation as follows:

$$\frac{d\,(E(X(t)))}{N - E(X(t))} = \lambda p(t) dt$$

$$\text{In}\left(\frac{N - E(X(t))}{N - \mathrm{X}(0)}\right) = -\lambda \int_0^{\mathrm{t}} p(t) dt.$$

Thus, we have the following equation of $E(X(t))$:

$$E(X(t)) = N - (N - X(0))\, e^{-\lambda \int_0^t p(\tau) d\tau}. \tag{4}$$

To derive $F(t)$, we use the same technique in [28]. Let us first define $H(t) = 1 - F(t)$. Then, $H(t)$ can be expressed as follows:

$$H(t+\Delta t) = H(t) \mathrm{P}\left\{\text{No delivery to dest. in } \Delta t | \mathrm{X(t)}\right\}$$

We take expectation for the aforementioned expression and have

$$H(t+\Delta t) = H(t) E\left(\mathrm{P}\left\{\text{No delivery to dest. in } \Delta t | \mathrm{X(t)}\right\}\right)$$
$$= H(t) E\left((e^{-\lambda \Delta t})^{X(t)}\right)$$

$$\dot{H}(t) = \lim_{\Delta t \to 0} \frac{H(t)\left(E\left((e^{-\lambda \Delta t})^{X(t)}\right) - 1\right)}{\Delta t} = -\lambda H(t) E(X(t))$$

$$H(t) = H(0) e^{-\lambda \int_0^t E(X(s)) ds}.$$

Therefore, we can obtain the following equation about $F(t)$:

$$F(t) = 1 - H(t) = 1 - e^{-\lambda \int_0^t E(X(s)) ds} \tag{5}$$

where $H(0) = 1$.

Now, we can specify the optimization problem of (1) under two-hop forwarding as follows:

$$\text{Maximize} \quad 1 - exp\left(-\lambda \int_0^T E(X(s))\, ds\right)$$
$$\text{Subject to} \quad \begin{cases} N - (N - X(0))\, e^{-\lambda \int_0^T p(\tau) d\tau} \le \Psi \\ 0 \le p(t) \le 1. \end{cases} \tag{6}$$

According to the monotonous of $F(t)$, we can transform the optimization problem in (6) to the following problem with a simple form:

$$\text{Maximize} \quad \int_0^T E(X(s))\, ds$$
$$\text{Subject to} \quad \begin{cases} \int_0^T p(\tau) d\tau \le \frac{1}{\lambda} \ln\left(\frac{N - X(0)}{N - \Psi}\right) \\ 0 \le p(t) \le 1. \end{cases} \tag{7}$$

B. Probabilistic Epidemic Forwarding

Now, we consider probabilistic epidemic forwarding. In Section III, we can see that, unlike in two-hop forwarding, in probabilistic epidemic forwarding, all nodes can forward the message to other nodes. Therefore, we can obtain the similar expression for the evolution of its state variable as follows:

$$X(t+\Delta t) = X(t) + \sum_{j=1}^{N - X(t)} \widehat{\varphi}_{t,t+\Delta t}(j) \tag{8}$$

where $\widehat{\varphi}_{t,t+\Delta t}(j)$ is defined as the same as $\varphi_{t,t+\Delta t}(j)$ but has a different value due to the difference from two-hop forwarding. According to probabilistic epidemic forwarding, we derive its expectation as follows:

$$E(\widehat{\varphi}_{t,t+\Delta t}(j)) = 1 - \left(1 - (1 - e^{-\lambda \Delta t}) p(t+\Delta t)\right)^{X(t)}.$$

To obtain the expectation $X(t)$, $E(X(t))$, we calculate the expectation of (8) on both sides, and with the help of formula transformation and taking the limits, we have the following equation:

$$\dot{E}(X(t)) = \lim_{\Delta t \to 0} \frac{(N - E(X(t)))\left(1 - \left(1 - (1 - e^{-\lambda \Delta t}) p(t)\right)^{X(t)}\right)}{\Delta t}$$
$$= \lambda (N - E(X(t)))\, E(X(t))\, p(t). \tag{9}$$

We solve (9) and have

$$E(X(t)) = \frac{N X(0) e^{\lambda N \int_0^t p(\tau) d\tau}}{N - X(0) + X(0) e^{\lambda N \int_0^t p(\tau) d\tau}}. \tag{10}$$

Notice that the transmission probability $F(t)$ of epidemic forwarding is the same as that of two-hop forwarding. Therefore, we can specify the optimization problem of (1) under probabilistic epidemic forwarding as follows:

$$\text{Maximize} \quad 1 - exp\left(-\lambda \int_0^T E(X(s))\, ds\right)$$
$$\text{Subject to} \quad \begin{cases} \frac{N X(0) e^{\lambda N \int_0^t p(\tau) d\tau}}{N - X(0) + X(0) e^{\lambda N \int_0^t p(\tau) d\tau}} \le \Psi \\ 0 \le p(t) \le 1. \end{cases} \tag{11}$$

Similarly, the aforementioned problem is simplified as

$$\text{Maximize} \quad \int_0^T E\left(X(s)\right) ds$$

$$\text{Subject to} \quad \begin{cases} \int_0^T p(\tau)d\tau \leq \frac{1}{\lambda N} \ln\left\{\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right\} \\ 0 \leq p(t) \leq 1. \end{cases} \tag{12}$$

V. Policy Design and Optimal Policy

In this section, we design the static and dynamic policies for the formulated optimal forwarding problems for both two-hop forwarding and probabilistic epidemic forwarding. For these two forwarding algorithms, we can express the optimization problem by a uniform form as follows:

$$\text{Maximize} \quad \int_0^T g(t)dt$$

$$\text{Subject to} \quad \begin{cases} \int_0^T p(t)dt \leq \vartheta \\ 0 \leq p(t) \leq 1 \end{cases} \tag{13}$$

where, for two-hop forwarding, the corresponding $g(t)$ and ϑ, denoted by $g_1(t)$ and ϑ_1, respectively, are given as follows:

$$\begin{aligned} g_1(t) &= N - (N - X(0))\, e^{-\lambda \int_0^t p(\tau)d\tau} \\ \vartheta_1 &= \frac{1}{\lambda} \ln\left(\frac{N - X(0)}{N - \Psi}\right) \end{aligned} \tag{14}$$

and for probabilistic epidemic forwarding, the corresponding $g(t)$ and ϑ, which are denoted by $g_2(t)$ and ϑ_2, respectively, are given as follows:

$$\begin{aligned} g_2(t) &= \frac{NX(0)e^{\lambda N \int_0^t p(\tau)d\tau}}{N - X(0) + X(0)e^{\lambda N \int_0^t p(\tau)d\tau}} \\ \vartheta_2 &= \frac{1}{\lambda N} \ln\left(\frac{\Psi\left(N - X(0)\right)}{X(0)(N - \Psi)}\right). \end{aligned} \tag{15}$$

Recall our defined three kinds of policies: 1) static policy; 2) continuous dynamic policy; and 3) threshold dynamic policy. For each kind of policy, we will investigate its optimal property based on the following lemma and theorem for the optimization problem of (13).

Lemma 1: Given a policy $p(t)$, consider the policy $p'(t)$ that satisfies $p'(t) \succeq p(t)$, which means that $p'(\tau) \geq p(\tau)$ for any $\tau \in [0, T]$. Then, $F'(T) \geq F(T)$ holds for both two-hop forwarding and probabilistic epidemic forwarding.

Proof: Because $p'(t) \succeq p(t)$, for given T, it holds that $\int_0^T p'(t)dt \geq \int_0^T p(t)dt$. Because $-exp(-\lambda x)$ increases with x, at the same time, it holds that $g_1'(T) \geq g_1(T)$ and $g_2'(T) \geq g_2(T)$ for two-hop forwarding and probabilistic epidemic forwarding, respectively. It then immediately follows that $F'(T) \geq F(T)$ for both two-hop forwarding and probabilistic epidemic forwarding. ■

Based on Lemma 1, we obtain the following theorem.

Theorem 1: If $T \geq \vartheta$, the optimal policy for both two-hop forwarding and probabilistic epidemic forwarding, which is denoted by $p^*(t)$, saturates the constraint, i.e., $\int_0^T p^*(t)dt = \vartheta$. However, if $T < \vartheta$, the optimal policy is $p(t) = 1$, which does not saturate the constraint.

Proof: First, we consider the case of $T \geq \vartheta$. Consider a policy $p(t)$ that is different from the optimal policy $p^*(t)$. It does not saturate the energy constraint, i.e., $\int_0^T p(t)dt < \vartheta$. Therefore, because $\exists\varepsilon$, $\int_0^T p(t)dt + \varepsilon \leq \vartheta$ holds. Because $T \leq \vartheta$, we get a new policy, which is denoted by $p\prime(t)$, i.e., $p\prime(t) = p(t) + \varepsilon/T$, which makes $\int_0^T p\prime(t)dt \leq \vartheta$ hold. It is obvious that $p\prime(t) \succeq p(t)$. Thus, by Lemma 1, we have $F'(T) \geq F(T)$, which means that $p\prime(t)$ is a better policy while satisfying the energy constraint than the policy $p(t)$, which proves the theorem, i.e., that the optimal policy saturates the constraint when $T \geq \vartheta$. Otherwise, the optimal policy is obviously $p(t) = 1$. ■

1) Static Policy: If the network administrator wants to use a simple policy to control the opportunistic forwarding, the static control can be used. In this section, we consider the static control, where $p(t)$ is assumed to be a constant α, i.e., $p(t) = \alpha$.

For *Theorem 1*, the condition of $T \leq \vartheta$ is obviously satisfied, because the energy constraint for the message delivery takes effect for the system. Otherwise, the optimal policy is $p(t) = 1$, which means that the message delivery energy is not constrained. Therefore, based on *Theorem 1*, we immediately have the static policy as follows:

$$p(t) = \alpha = \frac{\vartheta}{T}. \tag{16}$$

Based on (14), we have the static policy for two-hop forwarding, which is denoted by $p_1^s(t)$, as follows:

$$p_1^s(t) = \frac{\vartheta_1}{T} = \frac{1}{\lambda T} \ln\left(\frac{N - X(0)}{N - \Psi}\right).$$

Similarly, based on (15), we can obtain the static policy for the epidemic forwarding, which is denoted by $p_2^s(t)$, as follows:

$$p_2^s(t) = \frac{\vartheta_2}{T} = \frac{1}{\lambda NT} \ln\left(\frac{\Psi\left(N - X(0)\right)}{X(0)(N - \Psi)}\right).$$

Therefore, when the energy constraint is given as Ψ, we can get the static control policy $p(t) = \alpha$ to maximize the message delivery probability. On the other hand, if our object is to achieve a certain message delivery probability, we can also obtain the control policy and energy constraint.

2) Continuous Dynamic Policy: The continuous dynamic policy is more complex than the static policy, because it varies with time. That is, according to the different network conditions at different times, it chooses a more suitable forwarding probability. For example, with the time elapsing, the number of message copies becomes larger. Therefore, we can decrease the forwarding probability to reduce the network traffic. To investigate the property of the dynamic optimal policy, we study two typical continuous functions: 1) the power function and 2) the exponential function. Without loss of generality, we set the power policy as $p(t) = \alpha t^\beta$ and set the exponential policy as $p(t) = \alpha e^{\beta t}$.

Under the power-function-based control, we can derive the policies for two-hop and probabilistic epidemic forwarding,

TABLE II
MAIN RESULTS OF THE OPTIMAL POLICIES

	Static policy	Power policy	Exponential policy	Optimal threshold policy
Two-hop	$p_1^s(t) = \frac{\ln\left(\frac{N-X(0)}{N-\Psi}\right)}{\lambda T}$	$p_1^p(t) = \frac{(\beta+1)\ln\left(\frac{N-X(0)}{N-\Psi}\right)t^\beta}{\lambda T^{\beta+1}}$	$p_1^e(t) = \frac{\beta\ln\left(\frac{N-X(0)}{N-\Psi}\right)e^{\beta t}}{\lambda(e^{\beta T}-1)}$	$p_1^t(t) = \begin{cases} 1, & t \le \vartheta_1 \\ 0; & t > \vartheta_1 \end{cases}$
Epidemic	$p_2^s(t) = \frac{\ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right)}{\lambda NT}$	$p_2^p(t) = \frac{(\beta+1)\ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right)t^\beta}{\lambda NT^{\beta+1}}$	$p_2^e(t) = \frac{\beta\ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right)e^{\beta t}}{\lambda N(e^{\beta T}-1)}$	$p_2^t(t) = \begin{cases} 1, & t \le \vartheta_2 \\ 0; & t > \vartheta_2 \end{cases}$

which is denoted by $p_1^p(t)$ and $p_2^p(t)$, respectively. In terms of $p_1^p(t)$, according to *Theorem 1* and (14), we have

$$\int_0^T p_1^p(t)dt = \int_0^T \alpha t^\beta dt = \vartheta_1 = \frac{1}{\lambda}\ln\left(\frac{N-X(0)}{N-\Psi}\right).$$

Thus, we have $\alpha = (\beta + 1/\lambda T^{\beta+1})\ln((N-X(0))/N-\Psi)$. Consequently, we obtain the expression for $p_1^p(t)$ as follows:

$$p_1^p(t)dt = \frac{\beta+1}{\lambda T^{\beta+1}}\ln\left(\frac{N-X(0)}{N-\Psi}\right)t^\beta. \tag{17}$$

Similar to deriving $p_1^p(t)$, according to *Theorem 1* and (15), we have

$$\int_0^T p_2^p(t)dt = \int_0^T \alpha t^\beta dt = \vartheta_2 = \frac{1}{\lambda N}\ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right).$$

Therefore, we have

$$p_2^p(t) = \frac{\beta+1}{\lambda NT^{\beta+1}}\ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right)t^\beta. \tag{18}$$

Similar to deriving the power policy $p_1^p(t)$ and $p_2^p(t)$, we can obtain the exponential policy for two-hop and probabilistic epidemic forwarding, which is denoted by $p_1^e(t)$ and $p_2^e(t)$, respectively, as follows:

$$p_1^e(t) = \frac{\beta}{\lambda(e^{\beta T}-1)}\ln\left(\frac{N-X(0)}{N-\Psi}\right)e^{\beta t}$$
$$p_2^e(t) = \frac{\beta}{\lambda N(e^{\beta T}-1)}\ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right)e^{\beta t}. \tag{19}$$

Based on intuition, we can infer that the dynamic policy performs better than the static policy. In the dynamic policies, the power and exponential policies would achieve different delivery probabilities. According to different settings of parameter β, both the power and exponential policies may have different performance levels (see Table II). In Section VI, we will investigate the performance of different policies by numerical results.

3) Threshold Dynamic Policy: In this section, we consider the threshold dynamic policy. Based on the definition of the threshold policy, we can see that the optimization parameter is the threshold t_0. Therefore, the goal is to find the threshold of time t_0, which maximizes the transmission probability. At the same time, we find that the threshold policy is the optimal policy among the static and dynamic policies for both two-hop and probabilistic epidemic forwarding. Therefore, we first prove its optimal and then derive its expression.

Theorem 2: The threshold dynamic policy is the optimal policy for both two-hop and probabilistic epidemic forwarding, i.e., $\hat{p}(t) = 1$ for $t \le \vartheta$ and $\hat{p}(t) = 0$ for $t > \vartheta$.

Proof: We concentrate on the optimization object expressed in (13), which is $\int_0^T g(t)dt$. First, we consider two-hop forwarding. The optimization object turns to $\int_0^T g_1(t)dt$. Let $P(t) = \int_0^t p(\tau)d\tau$. Based on the expression of $g_1(t)$ in (14), we can have $\int_0^T g_1(t)dt = f_1(P(t))$, where $f_1(x) = NT - (N - X(0))\int_0^T exp(-\lambda x)dx$. Based on this expression of $f_1(x)$, we can see that $f_1(x)$ increases with x. Therefore, we have $\int_0^T g_1(t)dt$, which increases with $P(t)$.

Then, we consider probabilistic epidemic forwarding. The optimization object is $\int_0^T g_2(t)dt$. Based on the expression of $g_2(t)$ in (15), we have

$$\int_0^T g_2(t)dt = NT - \int_0^T f_2\left(exp\left(N\lambda P(t)\right)\right)dt$$

where $f_2(x) = (N(N-X(0))/N - X(0) + X(0)x)$. We can see that $f_2(x)$ decreases with x. Therefore, $\int_0^T g_2(t)dt$ increases with $P(t)$.

Combining the monotonicity of $\int_0^T g_1(t)dt$ and $\int_0^T g_2(t)dt$ for two-hop and probabilistic epidemic forwarding, respectively, the following condition holds. For $P(t)$, if there exists $\hat{P}(t) \succeq P(t)$, then the corresponding $\int_0^T \hat{g}(t)dt \ge \int_0^T g(t)dt$ for both two-hop and epidemic forwarding. At the same time, we notice that $P(t)$ is a nondecreasing function and has the constraint of $P(T) = \vartheta$ when the corresponding policy $p(t)$ is optimal. Therefore, the optimal $P(t)$ exists when $\{\min .t|P(t) = \vartheta, 0 \le t \le T\}$. We notice that $0 \le p(t) \le 1$; therefore, $\min .t = \vartheta$. Then, the corresponding optimal forwarding policy is $\hat{p}(t) = 1$ for $t \le \vartheta$ and $\hat{p}(t) = 0$ for $t > \vartheta$. This obtained optimal policy is the threshold dynamic policy as defined in Definition 2, which proves the theorem. ■

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According to Theorem 2, we have the optimal threshold policies for two-hop and probabilistic epidemic forwarding, which is denoted by $p_1^t(t)$ and $p_2^t(t)$, respectively, as follows:

$$p_1^t(t) = \begin{cases} 1, & t \leq \frac{1}{\lambda} \ln\left(\frac{N-X(0)}{N-\Psi}\right) \\ 0, & t > \frac{1}{\lambda} \ln\left(\frac{N-X(0)}{N-\Psi}\right) \end{cases}$$

$$p_2^t(t) = \begin{cases} 1, & t \leq \frac{1}{\lambda N} \ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right) \\ 0, & t > \frac{1}{\lambda N} \ln\left(\frac{\Psi(N-X(0))}{X(0)(N-\Psi)}\right). \end{cases} \tag{20}$$

VI. Performance Evaluation

In this section, we give the performance evaluation. First, through both simulation and numerical results, we demonstrate the accuracy of our analysis model by comparing the theoretical results obtained by our continuous-time model and DSC–DTN in [28]. Then, by the numerical results, we evaluate the performance of the obtained forwarding policies, including the static policy, the continuous dynamic policy, and the threshold dynamic policy, for two-hop and probabilistic epidemic forwarding. At the same time, we compare the performance of two-hop and probabilistic epidemic forwarding under the same policy, such as the static and threshold dynamic policies. Finally, we compare our static and optimal threshold policies with the approach without considering the message delivery energy constraint to show the efficiency of our scheme.

A. Evaluation Environment and Settings

We obtain the results by simulating the continuous-time system with Matlab. The important parameters in our evaluation include the mobility-model-related exponential parameter of ICT λ, energy constraint Ψ, and the number of nodes in the network N. In terms of mobility model, we choose the DTN application of vehicular ad hoc networks and perform the evaluation based on the mobility model obtained from the chosen application. In particular, we consider the real motion traces from about 2100 operational taxis for about 1 mo in Shanghai City collected by the Global Positioning System (GPS) [38]. The location information of the taxis is recorded at every 40 s within the area of 102 km^2. By analyzing the large amount of trace data, Zhu *et al.* in [36] and Lee *et al.* in [35] find that the distribution of ICT between taxis follows the exponential distribution on a large range of timescale. Consequently, this result implies that the chosen application of vehicular network is appropriate for evaluating our obtained policies. In [36], to establish an accurate mobility model from the traces, the authors perform a least squares fitting to identify the exponential parameter and find that the ICT is well approximated by the exponential distribution of $P\{X > t\} = e^{-3.71\times10^{-6}t}$. Therefore, in our simulation, we set parameter $\lambda = 3.71 \times 10^{-6}$ s^{-1}.

In the evaluation of the proposed policies, the *first set* of parameter settings are as given follows: $\Psi = 20$ for two-hop forwarding and $\Psi = 50$ for epidemic forwarding, $N = 200$, T varies from 0 s to 150 000 s, and $\lambda = 3.71 \times 10^{-6}$ s^{-1}. However, in the comparison of our model with the approach in [28], we also use the *second set* of parameter settings, where λ is changed to 1.0453×10^{-5} s^{-1} to set the parameters to the same values as in [28].

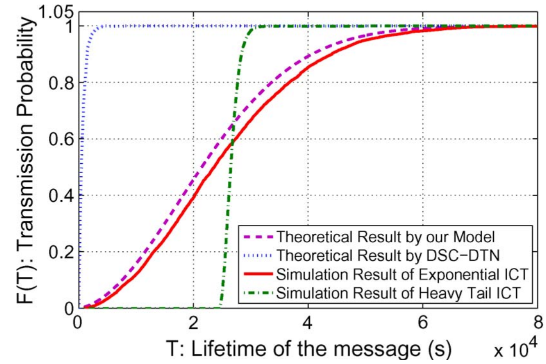

Fig. 1. Simulation and theoretical results of both our model and DSC–DTN under the first set of parameter settings.

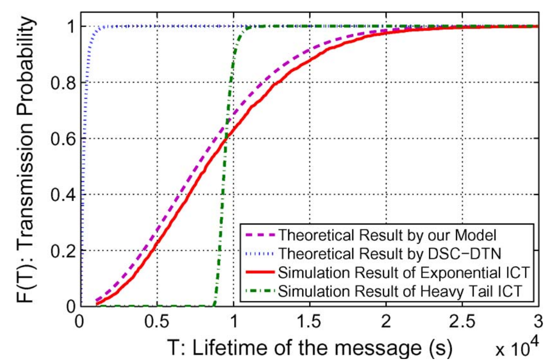

Fig. 2. Simulation and theoretical results of both our model and DSC–DTN under the second set of parameter settings.

B. Validation of the Model's Accuracy

In this section, we evaluate the accuracy of our continuous-time Markov model by comparing the simulation and theoretical results. The simulation results were obtained by simulating the continuous-time system according to the parameters settings. Without loss of generality, we set the forwarding policy $p(t) = 1$ because our goal is to verify the accuracy of the theoretical model. At the same time, we also show the theoretical result obtained by the closed form of in DSC–DTN by the discrete-time model. Consequently, the forwarding algorithm studied in DSC–DTN is two-hop forwarding, and therefore, our algorithm assumes two-hop forwarding in order to compare. As stated in the related work in Section II, recent works that model the human mobility indicate that the ICT follows heavy-tailed distribution. Although the ICT follows exponential distribution in our targeted application of vehicle networks, we also investigate the effect of heavy-tailed distribution on the system performance. Here, we use a classic heavy-tailed distribution, i.e., the Pareto distribution with a distribution function of $F(x) = 1 - (b/x)^a (x >= b)$. We set $a = 1.1$ and set b to be the value that achieves the same mean with the exponential distribution used in the simulation. The results for the *first* and *second sets* of parameters are shown in Figs. 1 and 2, respectively.

Comparing the simulation and theoretical results, we can see that the message transmission probability of our model is close

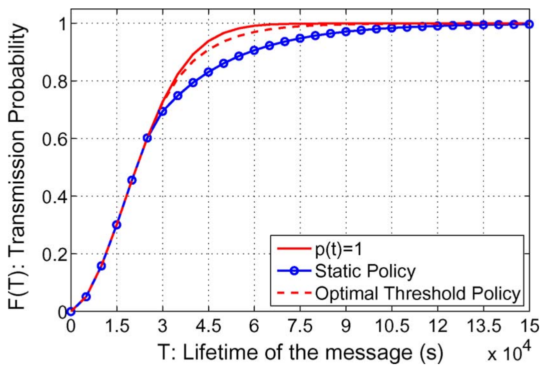

Fig. 3. Numerical results of the static policy (blue line), the threshold policy, and $\mathrm{p(t)} = 1$ (red solid line) in two-hop forwarding.

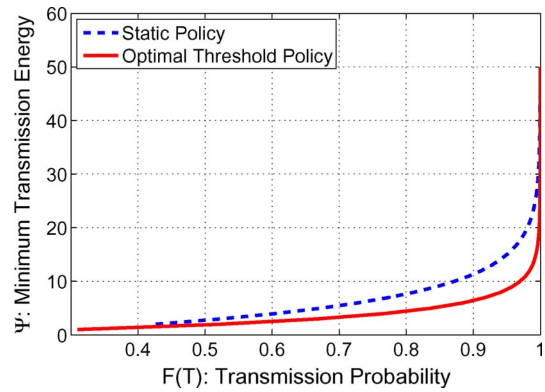

Fig. 4. Numerical results of the minimum-energy constraint versus the transmission probability in two-hop forwarding when $\mathrm{T} = 10\,000$.

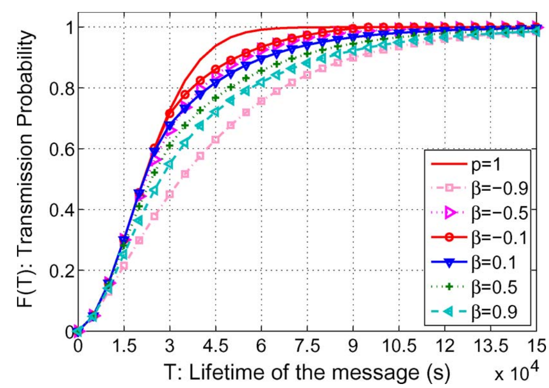

Fig. 5. Numerical results of the dynamic power policies with different parameters of β in two-hop forwarding.

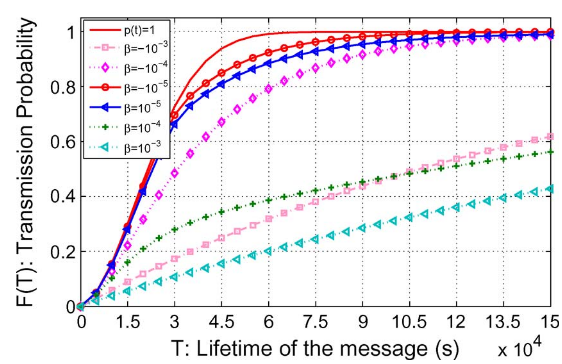

Fig. 6. Numerical results of the dynamic exponential policies with different parameters of β in two-hop forwarding.

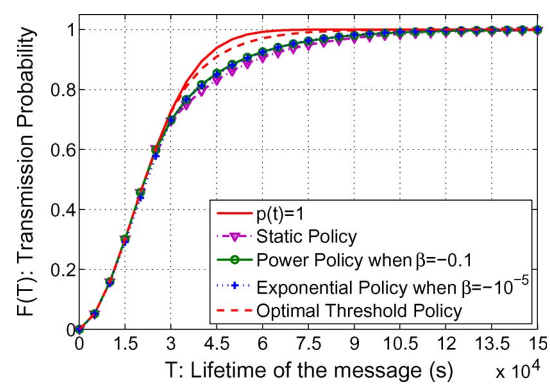

Fig. 7. Numerical results of the comparison among the static, power, exponential, and threshold dynamic policies in two-hop forwarding.

to that obtained by simulation, and the average deviation between the simulation and theoretical results is about 4.22% and 3.78% for the *first* and *second sets* of parameters, respectively. This result demonstrates the accuracy of the derived closed form of delivery probability by (5) and further demonstrates the accuracy of our continuous-time Markov model. For this reason, we use the numerical results in the performance evaluation of different policies. However, the theoretical results derived by the discrete-time model in DSC–DTN are far from the simulation results. As the authors' explain, the closed form provided in [28] can only infer some properties of the system but is rather poor in evaluating the system performance. On the other hand, we can see that our model is accurate enough for the performance evaluation. Therefore, we conclude that our continuous-time model is much more accurate in modeling this DTN-based communication system. Related to the heavy-tailed distributed ICT, its behavior is very different from the exponential ICT. We can observe that its message transmission probability very quickly increases from 0 to 1 when the lifetime of the message is larger than a certain value. The reason is that, in the heavy-tailed distributed ICT, although there are some nodes that encounter each other with a long ICT, most of the users will have a shorter ICT than the exponential distribution when their means are the same. Therefore, their system performance levels are different.

C. Numerical Results for Two-Hop Forwarding

Under the *first set* of parameter settings, we get the numerical results of the static, power, exponential, and optimal threshold policies and their comparison under two-hop forwarding, as shown in Figs. 3–7.

Fig. 3 shows the static and optimal threshold policies with the message transmission probability $F(T)$ according to the message lifetime T. The solid red line is obtained with $p(t) = 1$, which means no energy constraint. It can be noticed that the transmission probability $F(T)$ of the static policy increases with the message lifetime T. With the energy constraint $\Psi = 20$, the transmission probability is about 80% when $T = 40\,000$ s. Moreover, we can see that, even when T is longer than $100\,000$ s, $F(T)$ is still less than 1. This condition means that the energy constraint is strict. On the other hand, we can conclude that the static control performs better for the energy-constrained opportunistic forwarding. However, the optimal threshold policy achieves a higher transmission probability. It is close to the curve of $p(t) = 1$, although the energy is constrained by 20. This condition demonstrates the efficiency of the theoretically obtained optimal threshold policy.

As stated in Section V-A, if our objective is to achieve a certain message delivery probability within the message lifetime T, we can also obtain the minimum energy constraint of our policies. We set $T = 10\,000$, and other parameters are the same with the *first set* parameters. We plot the results in Fig. 4. Based on the results, we can observe that the minimum energy needed by the static policy is larger than the optimal threshold policy. In particular, when $0.8 \le F(T) \le 1$, the optimal threshold policy performs much better than the static policy. For example, when $F(T) = 0.9$, the Ψ needed by the static policy is 10.5, whereas the threshold policy only needs 6, which is about half the static policy.

Figs. 5 and 6 show the power and exponential policies with different β. In the power policy, when β is negative, the corresponding policy performs better with the increase of β. The opposite conclusion can be obtained when β is positive. Comparing all lines, we can see that the negative β will give better system performance when the absolute values of β are the same. For example, the line of $\beta = -0.1$ performs better than that of $\beta = 0.1$. The reason is that, when β is negative, the control policy is a decreasing function. In the network, the number of copies become larger with the time elapsing. Because the decreasing policy can reduce the forwarding probability to reduce the network traffic, it would get better performance. In the exponential policies, we can obtain a similar conclusion. However, because the exponential function increases or decreases much faster than the power function, we should set the absolute value of β to be as small as 10^{-5} to get a relatively better performance.

Fig. 7 gives the performance comparison between the static, continuous dynamic, and optimal threshold policies, where the dynamic policies include the power policy with $\beta = -0.1$ and the exponential policy with $\beta = -10^{-5}$. Based on the results, we can obtain that the static policy performs the worst. The reason is that the static policy uses a constant probability to control the opportunistic forwarding. However, it is simple and can be used in some resource-constrained environment. If we want to get a higher transmission probability, we can use more complicate continuous dynamic policies such as the power and exponential policies with suitable β. Based on the results, we can obtain that the negative-power policy is suitable for controlling opportunistic forwarding. However, the results show that the threshold policy achieves the best performance among all policies, which demonstrates the correctness of *Theorem 2*.

D. Numerical Results for Probabilistic Epidemic Forwarding

In this section, we give the numerical results of the proposed policies for probabilistic epidemic forwarding. Similar to two-hop forwarding, we study the static, continuous dynamic, and threshold policies. The *first set* of parameters is used, and the numerical results are shown in Figs. 8–12.

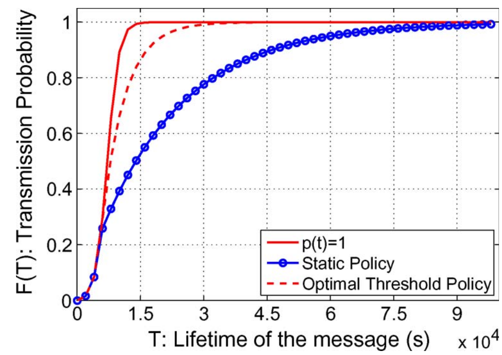

Fig. 8. Numerical results of our proposed static policy (blue line), threshold policy, and $\mathrm{p(t)} = 1$ (red solid line) in probabilistic epidemic forwarding.

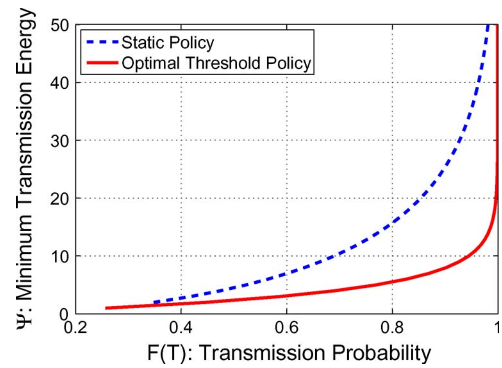

Fig. 9. Numerical results of the minimum-energy constraint versus the transmission probability in epidemic forwarding when $T = 80\,000$.

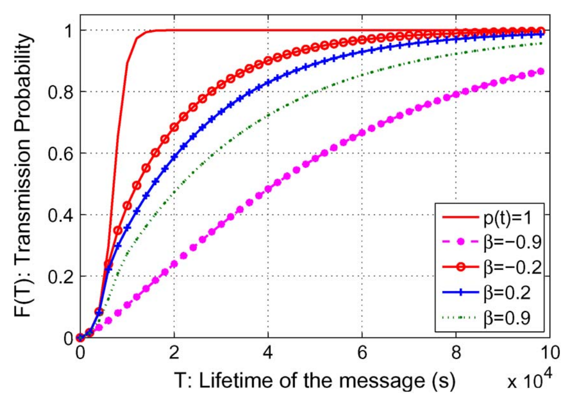

Fig. 10. Numerical results of the continuous dynamic power policies with different parameters β in probabilistic epidemic forwarding.

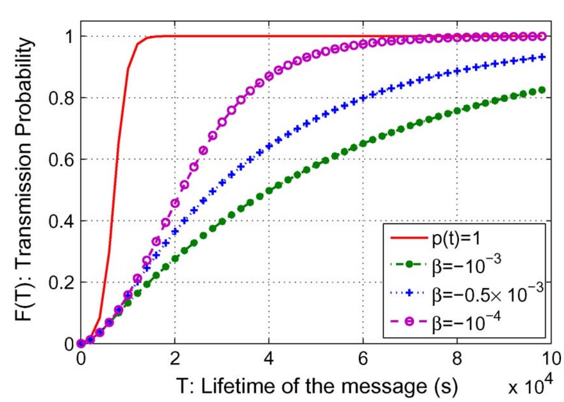

Fig. 11. Numerical results of the continuous dynamic exponential policies with different parameters β in probabilistic epidemic forwarding.

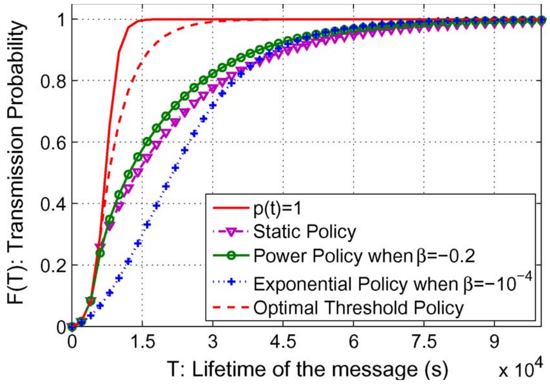

Fig. 12. Numerical results of the comparison between the static policy, continuous power policy with $\beta = -0.2$, exponential policy with $\beta = -10^{-4}$, and threshold dynamic policy in probabilistic epidemic forwarding.

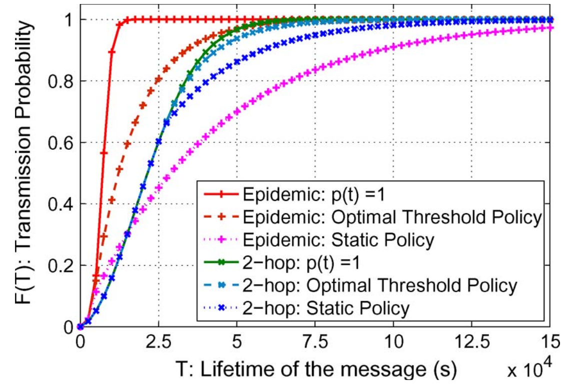

Fig. 13. Comparing between two-hop forwarding and probabilistic epidemic forwarding.

Fig. 8 shows the optimal static policy ($p(t) = \alpha$), with the message delivery probability $F(T)$ according to the message lifetime T. The red line is the delivery probability when $p(t) = 1$. The blue line is obtained by the static policy. We can obtain the same conclusion as in two-hop forwarding that the static policy cannot provide good performance for energy-constrained epidemic opportunistic forwarding because it does not change with time t. However, the optimal threshold policy provides much better performance than the static policy. To better demonstrate this result, we set $T = 80\,000$ s and plot the results of the minimum message transmission energy needed by the static and threshold policies in Fig. 9. Based on the results, we can obtain the same conclusion with two-hop forwarding that the optimal threshold policy provides better performance on the message transmission energy saving, although the energy saving gain of probabilistic epidemic forwarding is larger.

Fig. 10 shows the dynamic power policies with different parameters β, which are equal to -0.2, -0.9, 0.2, and 0.9, respectively. Based on the figure, we obtain the same results as in two-hop forwarding that, when the absolute value of β is the same, the negative β gives better performance than the positive β. On the other hand, we can see that, if β is 0.9, the transmission probability is about 80%, even when the lifetime is $T = 80\,000$ s. Therefore, in practice, we should use the power function with negative β. In the exponential policies shown in Fig. 11, we can see that it is not suitable to control the epidemic forwarding because of lower probability, even with a small parameter β. To compare with the optimal static, continuous dynamic, and optimal threshold policies, we plot Fig. 12. Based on the results, we can obtain that the optimal dynamic power policy with $\beta = -0.4$ is better than the static policy. However, unlike in two-hop forwarding, the static policy is even better than the exponential policy with $\beta = -10^{-4}$. It is because, in epidemic forwarding, the message is disseminated very fast. Therefore, it is hard to use the exponential function to control. Based on the aforementioned numerical results, we can conclude that the negative-power policy is also suitable for probabilistic epidemic forwarding, whereas the optimal threshold policy gives the best performance.

E. Two-Hop Versus Probabilistic Epidemic Forwarding

To compare the performance of two-hop forwarding and probabilistic epidemic forwarding, we use the *first set* of parameter settings and let energy constraint $\Psi = 20$ be the same with two-hop and probabilistic epidemic forwarding. We obtain the performance of the static and dynamic threshold policies, as shown in Fig. 13. Obviously, when the energy is not constrained, the transmission probability of epidemic forwarding is much higher than the transmission probability of two-hop forwarding. We can obtain this condition by the two curves of $p(t) = 1$. When the energy is constrained, under the respective optimal threshold policies, the performance of the epidemic forwarding is always better than two-hop forwarding with a different message's lifetime T. However, under the respective static policies, two-hop forwarding may obtain a higher transmission probability when the message's lifetime T is smaller than $10\,000$ s compared with the epidemic forwarding. The reason is that the transmission probability is limited by epidemic forwarding when T is small. When T is larger than $10\,000$ s, epidemic forwarding obtains better performance. Therefore, overall, epidemic forwarding is better than two-hop forwarding, even under the condition that the message delivery energy is constrained.

F. Transmissions Saving

In the aforementioned analysis, the results are compared with different forwarding policies. Now, we compare our scheme with the approach without the consideration of energy constraint to show the efficiency of our scheme in terms of message delivery energy savings. We use the *first set* of parameter settings and plot the number of message transmissions according to the achieved transmission probability with the increase of time t. This way, we can easily obtain the relationship between the message transmission times and the achieved transmission probability.

Fig. 14 shows the results of two-hop forwarding, where $p(t) = 1$ is the performance of the scheme that does not consider the energy constraint. Based on the results, we observe that the number of message transmissions of our static and optimal threshold policies is limited to 20 when $F(t)$ tends to 1, which is the energy constraint of the system. When $F(t) = 0.6$,

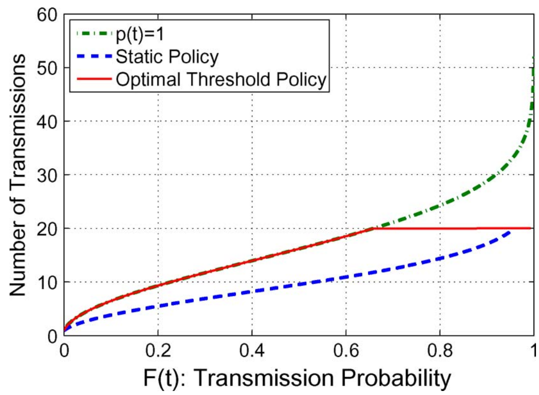

Fig. 14. Results of the varying transmission time with time T in two-hop forwarding.

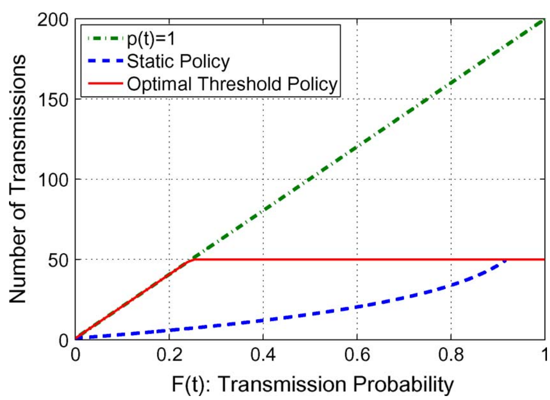

Fig. 15. Results of the varying transmission time with time T in probabilistic epidemic forwarding.

the number of transmissions of the static policy, which is about 10, is smaller than the number of transmissions of the threshold policy, which has the same number of transmissions with the scheme that does not consider the energy constraint. The reason is that, in our threshold policy, when $t < \vartheta$, the message is forwarded with a probability of 1. However, with the increase of $F(t)$, the number of transmissions of the threshold policy tends to a constant. When $F(t)$ tends to 1, the number of transmissions of the threshold policy is 20, whereas the number of transmissions of the scheme that does not consider the energy constraint is larger than 40. Therefore, our approach saves the number of message transmissions and still provides $F(t)$ that is very close to 1. At the same time, we can observe that the static policy can only achieve the transmission probability of about 92%, although its transmissions slowly increase. Based on the results shown in Fig. 15, we can obtain similar results about the efficiency of our scheme for probabilistic epidemic forwarding, although it has higher gains in terms of message transmission savings than two-hop forwarding.

VII. Conclusion

In this paper, we have introduced a continuous-time Markov model to analyze the problem of the energy-efficient optimal opportunistic forwarding policies in the DTNs. Through the theoretically analysis, proof, and extensive numerical results, we conclude that, for both two-hop forwarding and probabilistic epidemic forwarding, the threshold dynamic policy is the best choice for achieving the highest transmission probability. At the same time, among the continuous dynamic control policies, we find that the negative-power-function-based policy is more suitable for controlling opportunistic forwarding than the exponential policy. When the system energy is given and the optimal threshold policy is used, epidemic forwarding is always better than two-hop forwarding. However, when the static policy is used, two-hop forwarding may obtain a higher transmission probability when the message's lifetime T is short.

Acknowledgment

The authors would like to thank P. R. Kumar of the Department of Electrical and Computer Engineering, University of Illinois, Urbana-Champaign, and W. Chen of the Department of Electronic Engineering, Tsinghua University, for their valuable comments.

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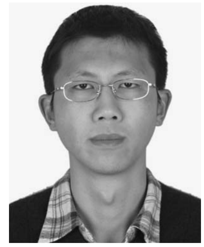

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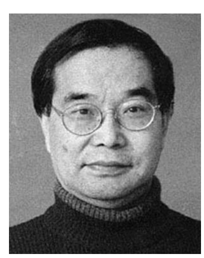

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